

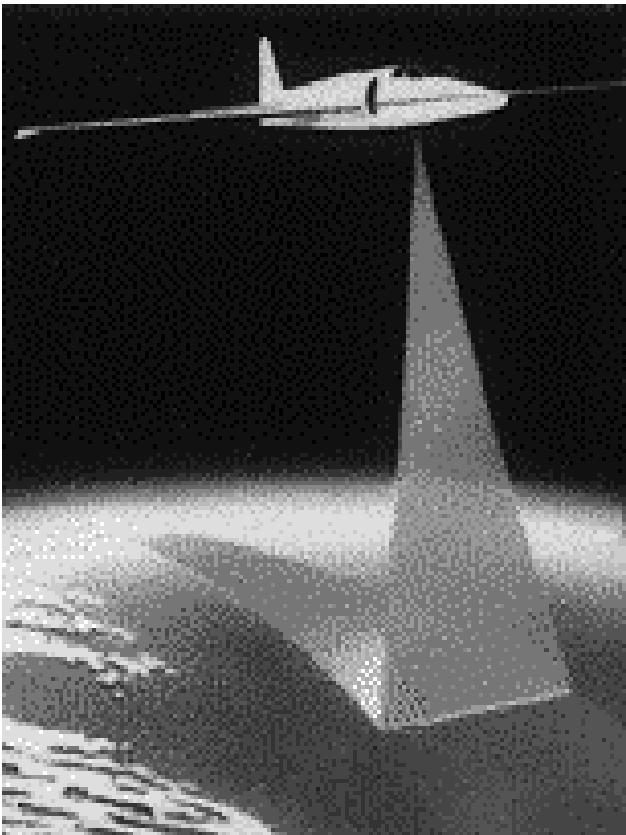
Compression of Hyperspectral Imagery

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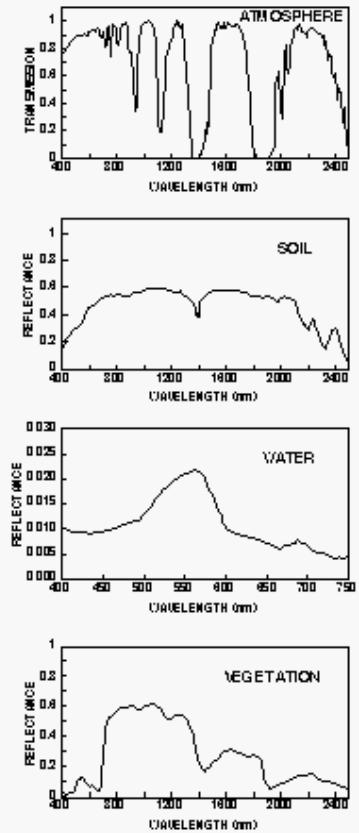
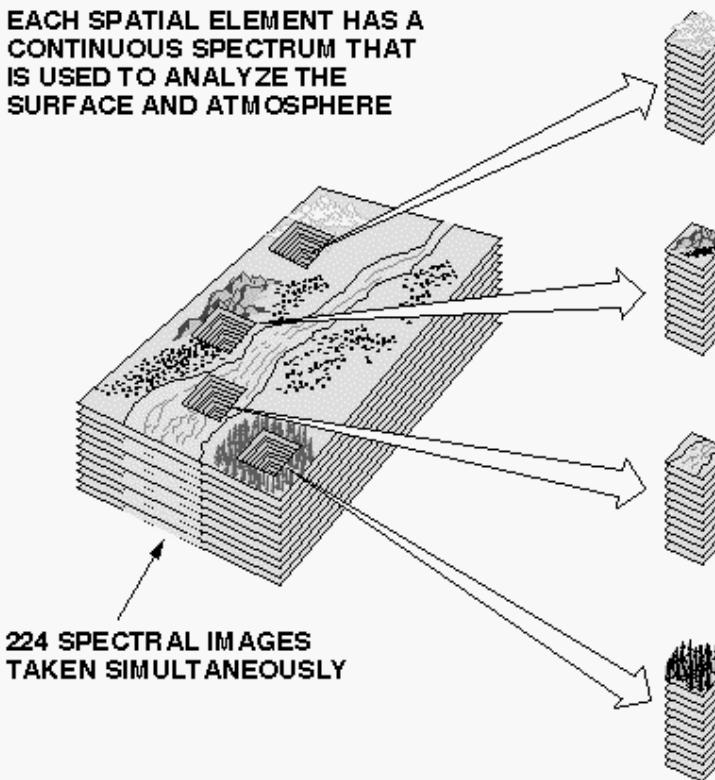
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Hyperspectral Images

- Measure reflected light in multiple bands
- Bands are narrow and contiguous
- A pixel is the spectral response of a large surface
- Correlation between spectral components
- Spatial correlation among adjacent spectra
- Ultraspectral technology promises sensors with spectral resolution hundreds of times higher



EACH SPATIAL ELEMENT HAS A CONTINUOUS SPECTRUM THAT IS USED TO ANALYZE THE SURFACE AND ATMOSPHERE



Applications

- Atmospheric analysis
- Burning biomasses detection
- Environmental hazards control

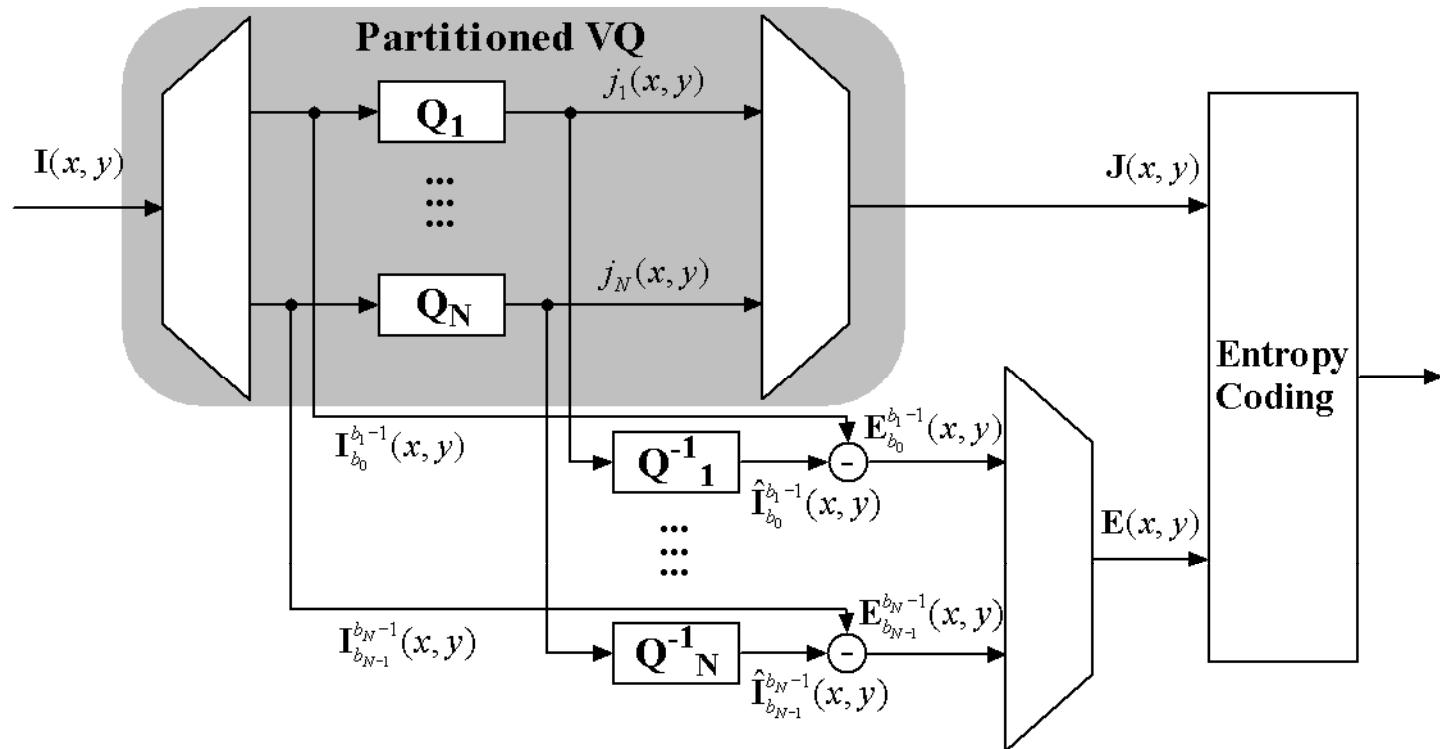
- Geological mapping
- Crop monitoring
- Intelligence

Requirements

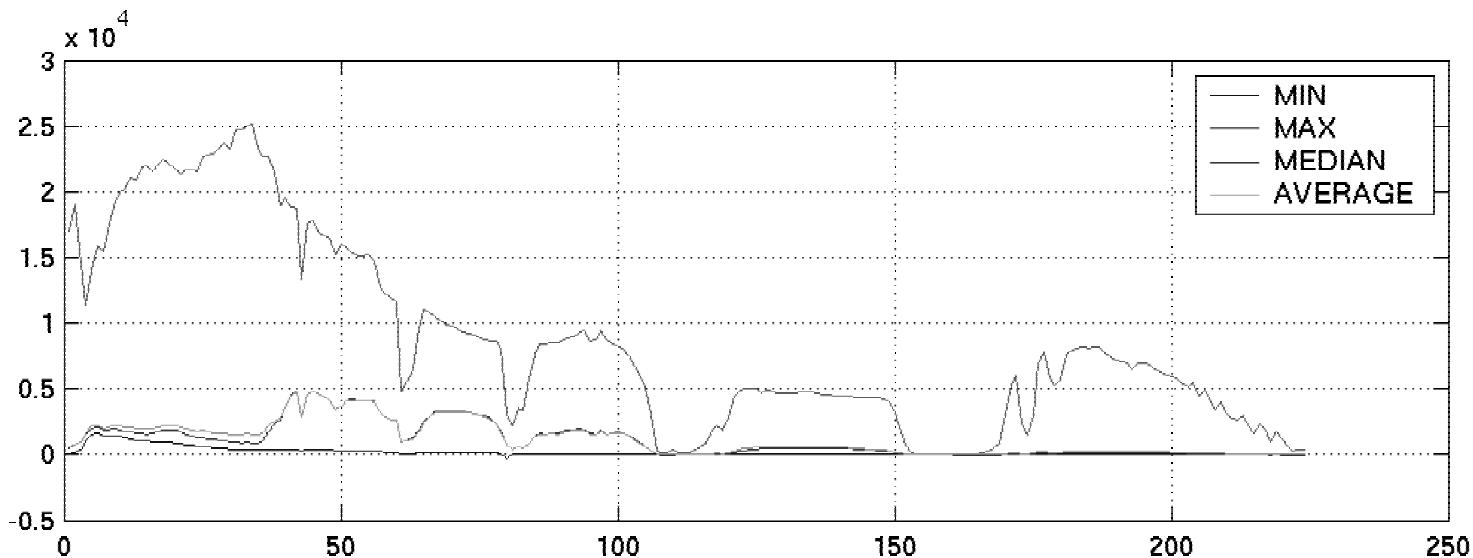
- Scalable to arbitrary resolution spectra
- Lossless and near-lossless compression
- Lossy compression with application-specific quality metrics
- Compressed stream suitable for
 - Progressive browsing
 - Data classification
 - Target detection

Proposed Approach

- Partitioned Vector Quantization
- Conditioned Entropy Coding of VQ indices and residuals



Partitioned Vector Quantization

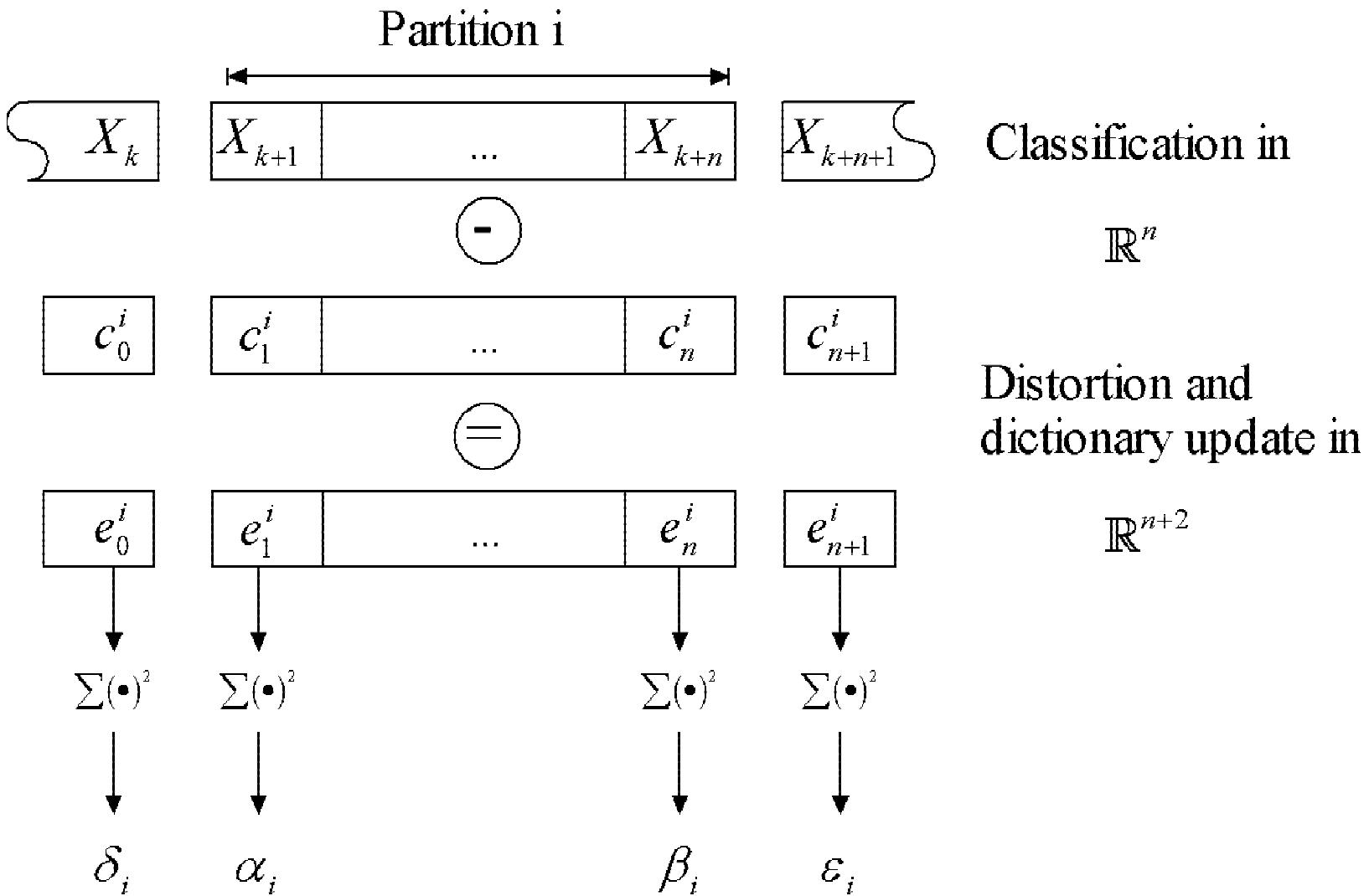


- Bands have very different statistics
- Vectors must be divided into variable size partitions
- Iterative design of codebooks, centroids and partitions minimizing

$$\|E(x,y)\|_2$$

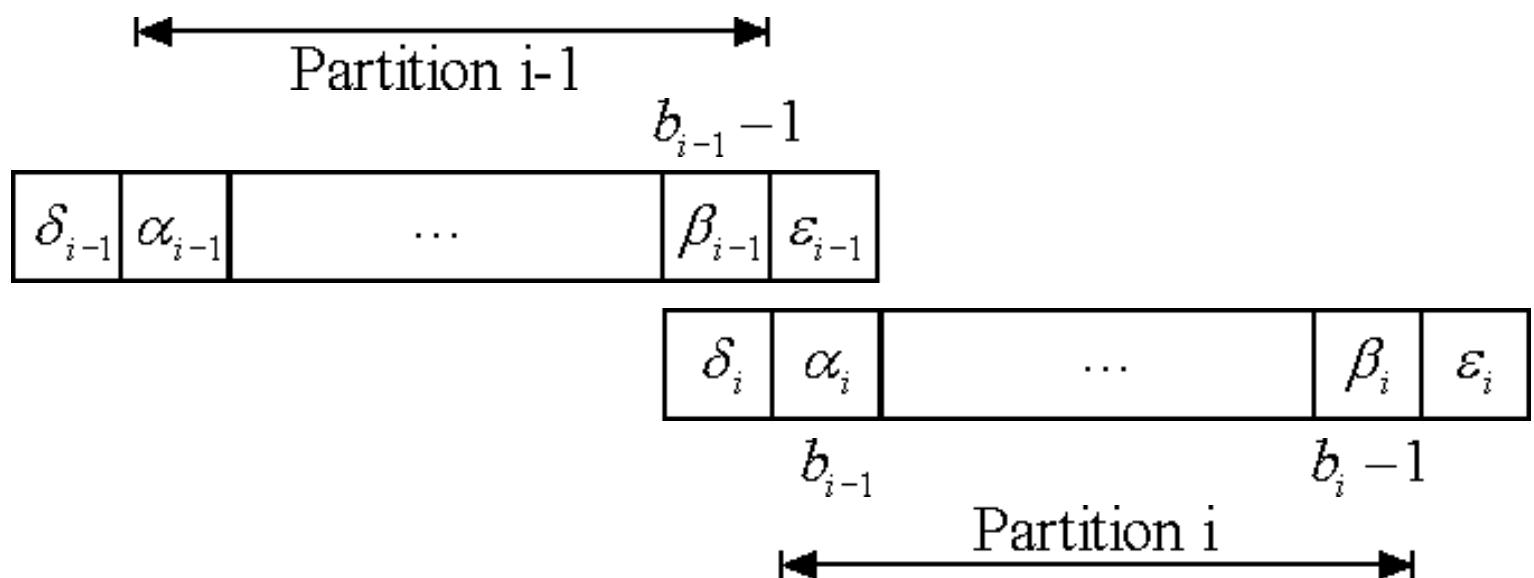
- Partitions quantized independently
- Spatial correlation exploited when encoding VQ indices

Partitioning Algorithm



Locally-optimal Partition Update

```
 $M_i = \min(\beta_{i-1} + \alpha_i, \beta_{i-1} + \varepsilon_{i-1}, \delta_i + \alpha_i);$ 
if( $M_i = \delta_i + \alpha_i$ )
     $b_{i-1} = b_{i-1} - 1;$ 
else if( $M_i = \beta_{i-1} + \varepsilon_{i-1}$ )
     $b_{i-1} = b_{i-1} + 1;$ 
```

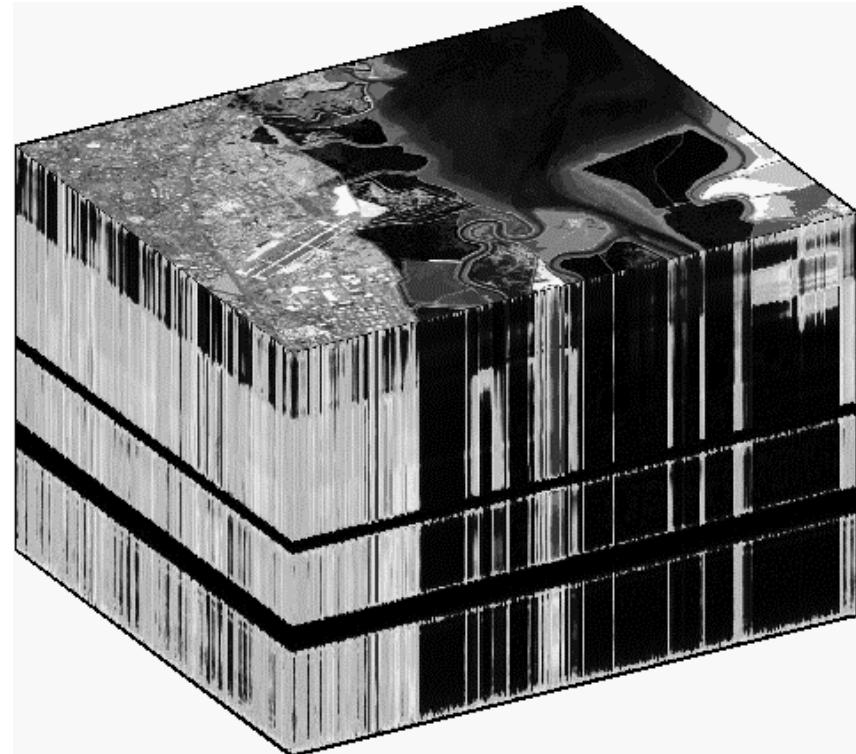


Experiments Setup and Entropy Coding

- Images composed by multiple scenes

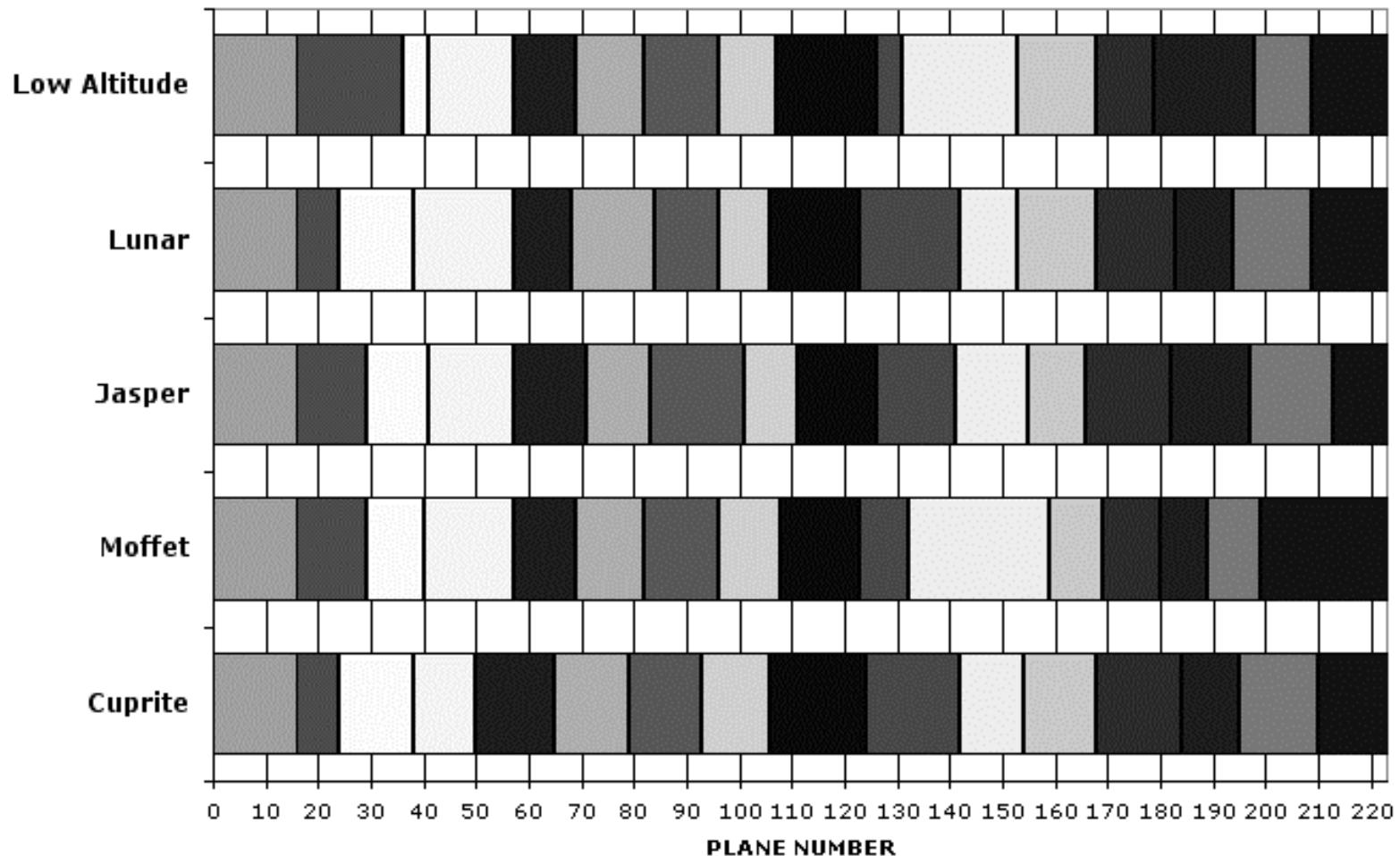
$$1 \text{ scene} = 614_{cols} \times 512_{rows} \times 224_{bands} \times 2_{bytes} \approx 135Mb$$

- 16 partitions
- 256 code-vectors/partition
- LOCO-I to encode LPVQ indices
- Residuals are encoded conditioned on the LPVQ indices



Partition Boundaries for Test Images

Bin Size and Alignment

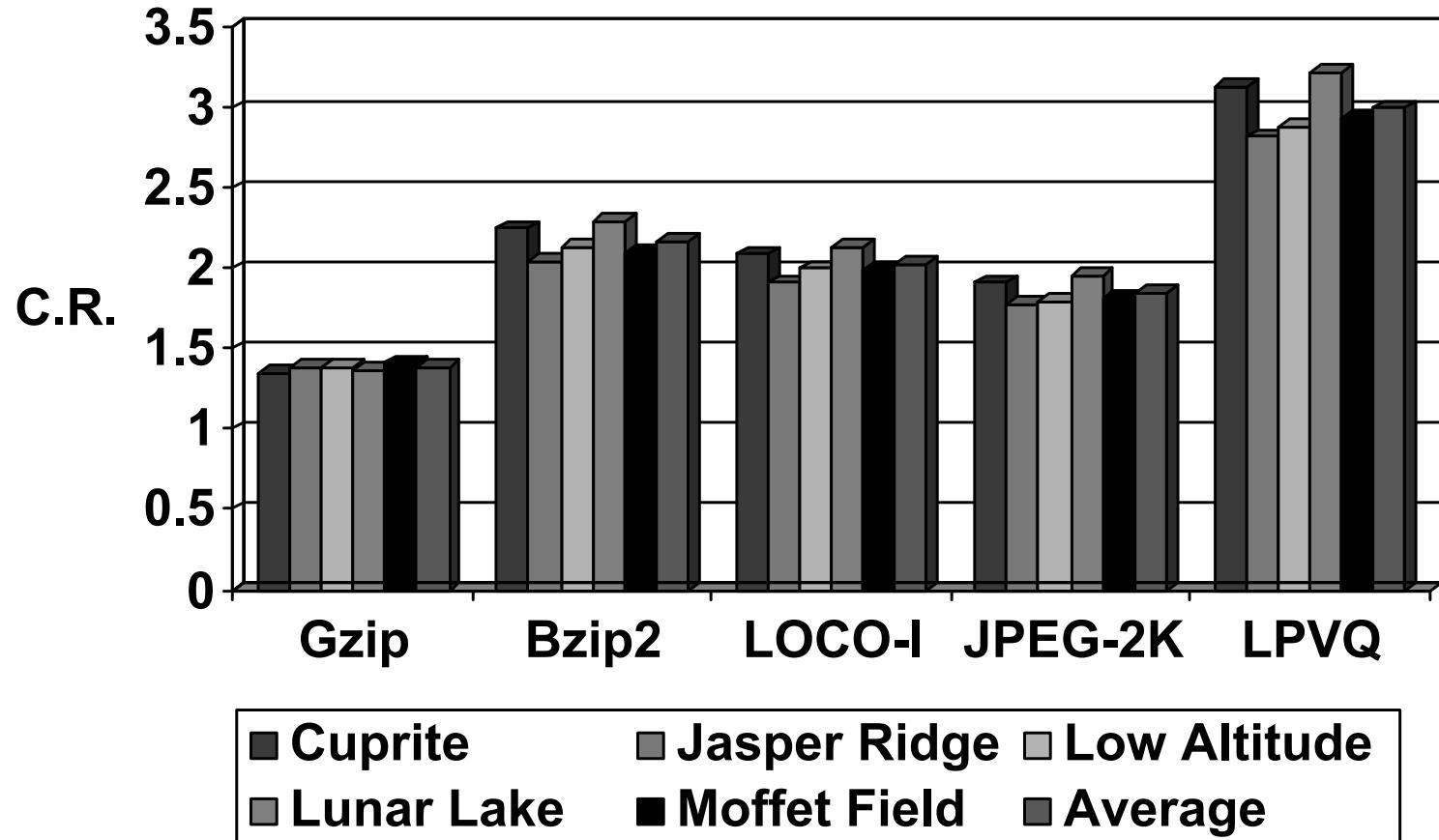


LPVQ Lossless Coding Results

AVIRIS	Lossless				
	Gzip	Bzip2	LOCO-I	JPEG-2K	LPVQ
Cuprite	1.35	2.25	2.09	1.91	3.13
Jasper Ridge	1.39	2.05	1.91	1.78	2.82
Low Altitude	1.38	2.13	2.00	1.80	2.89
Lunar Lake	1.36	2.30	2.14	1.96	3.23
Moffet Field	1.41	2.10	1.99	1.82	2.94
Average	1.38	2.17	2.03	1.85	3.00

$$\text{Compression Ratio} = \frac{\text{Size of input file}}{\text{Size of compressed file}}$$

LPVQ Lossless Coding Results



$$\text{Compression Ratio (C.R.)} = \frac{\text{Size of input file}}{\text{Size of compressed file}}$$

LPVQ Lossy Compression

AVIRIS	Indices 28:1	
	C.R.	SQNR(dB)
Cuprite	40.44	23.91
Jasper Ridge	35.02	20.37
Low Altitude	39.10	25.48
Lunar Lake	47.03	27.15
Moffet Field	40.92	25.74
Average	40.50	24.53

$$\text{SQNR(dB)} = \frac{10}{D} \sum_{i=0}^{D-1} \log_{10} \left(\frac{\sigma_{I_i}^2}{\sigma_{E_i}^2 + \frac{1}{12}} \right)$$

Comparisons with Ryan and Arnold (1997)

AVIRIS	ADC (bit)	0-order Entropy	Compression Ratio	
			M-NVQ	LPVQ
Cuprite 97	12	12.00	-	3.13
Jasper Ridge 89	10	8.28	3.31	-
Jasper Ridge 90	10	9.79	2.79	-
Jasper Ridge 97	12	11.21	-	2.82
Low Altitude 96	12	11.28	-	2.89
Lunar Lake 89	10	10.89	2.74	-
Lunar Lake 97	12	12.11	-	3.23
Moffet Field 89	10	9.04	2.71	-
Moffet Field 90	10	9.64	2.82	-
Moffet Field 97	12	11.20	-	2.94

* M. H. Ryan and J. F. Arnold (1997, May) "The Lossless Compression of AVIRIS Images by Vector Quantization", IEEE Trans. On Geoscience and Remote Sensing 35(3), 546-550.

Near-lossless Compression

Application-independent alternative to lossless coding

- Based on residual quantization
- Exact bounds on the coding error

Error measures for the i^{th} band:

- Maximum Absolute Error (MAE):

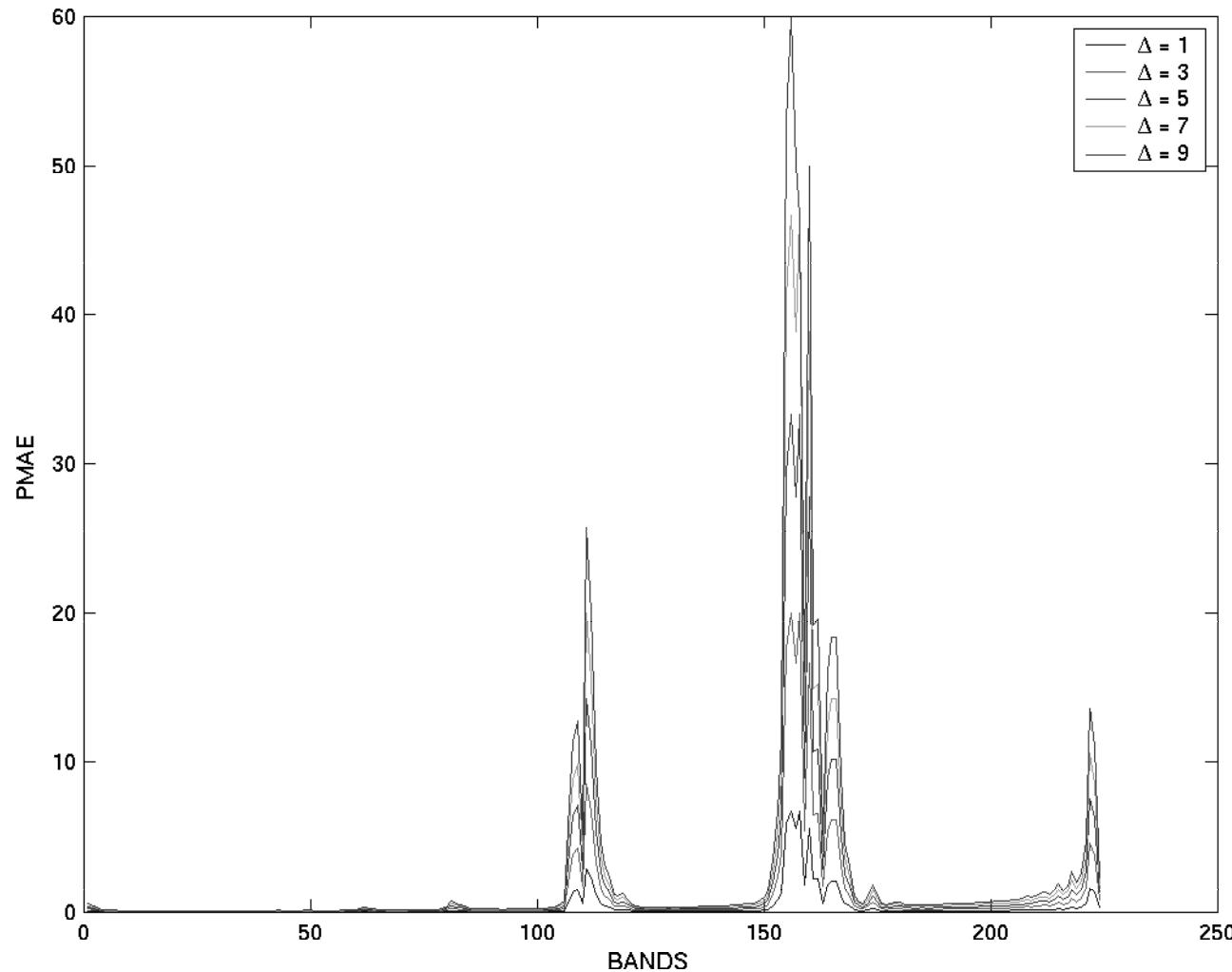
$$MAE_i = \max_{x,y} |I_i(x,y) - \hat{I}_i(x,y)| \square$$

- Percentage Maximum Absolute Error (PMAE):

$$PMAE_i = \frac{MAE_i}{D_i} \times 100 \square$$

Where D_i is the dynamic of the band

Near-lossless with Constant-PMAE



Note PMAE scale maximum

Constant-PMAE

Quantization step Δ_i proportional to $D_i \square$

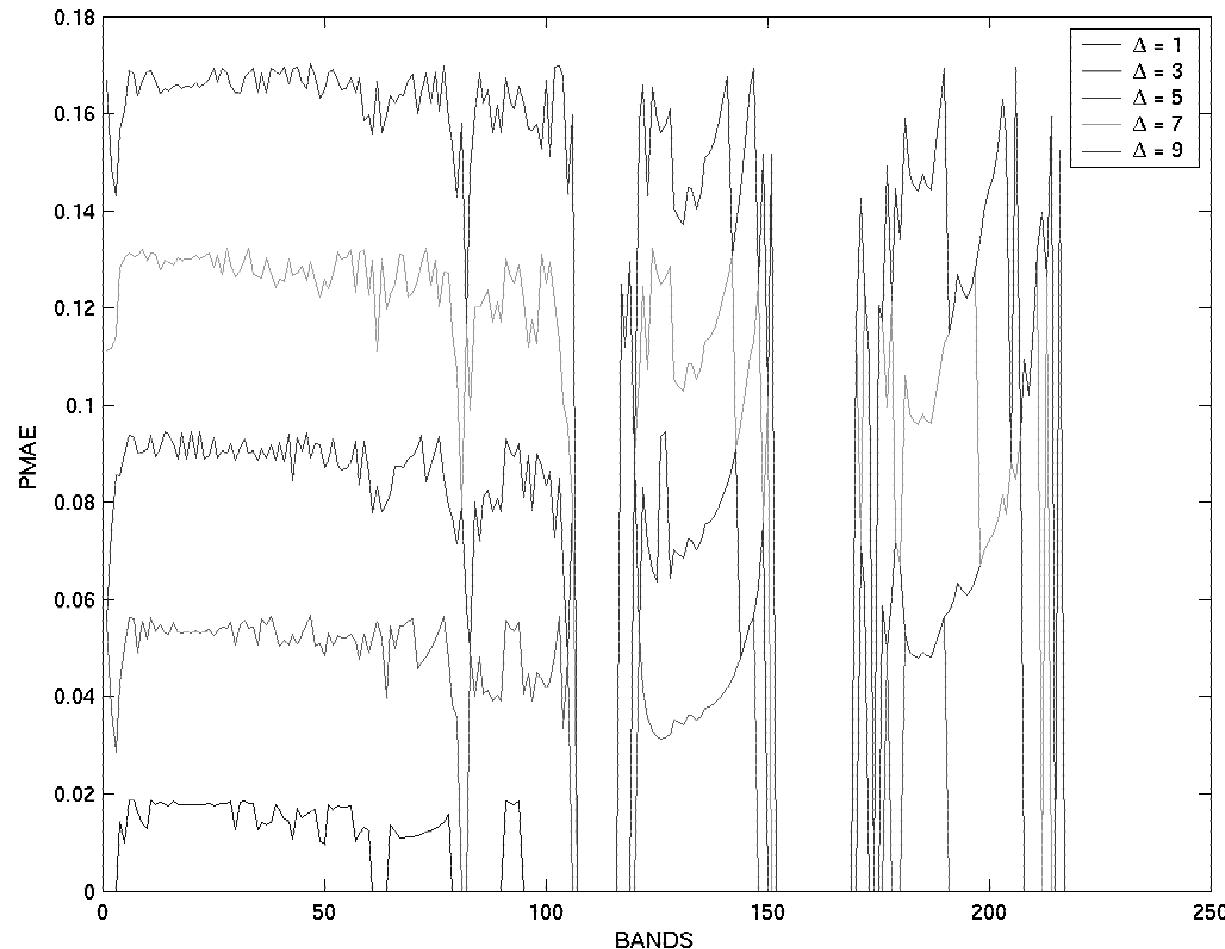
$$\Delta_i = \left\lfloor \rho \cdot D_i + \frac{1}{2} \right\rfloor$$

Image quality controlled by the global parameter Q :

$$Q \approx \frac{1}{D} \sum_{i=1}^D \Delta_i$$

$$\rho = \frac{D \cdot Q}{\sum_{i=1}^D D_i}$$

PMAE in Constant-PMAE Mode



Scale maximum is 0.18 vs. 60 achieved with constant-PMAE mode

Constant-SQNR

Quantization step Δ_i is the solution of:

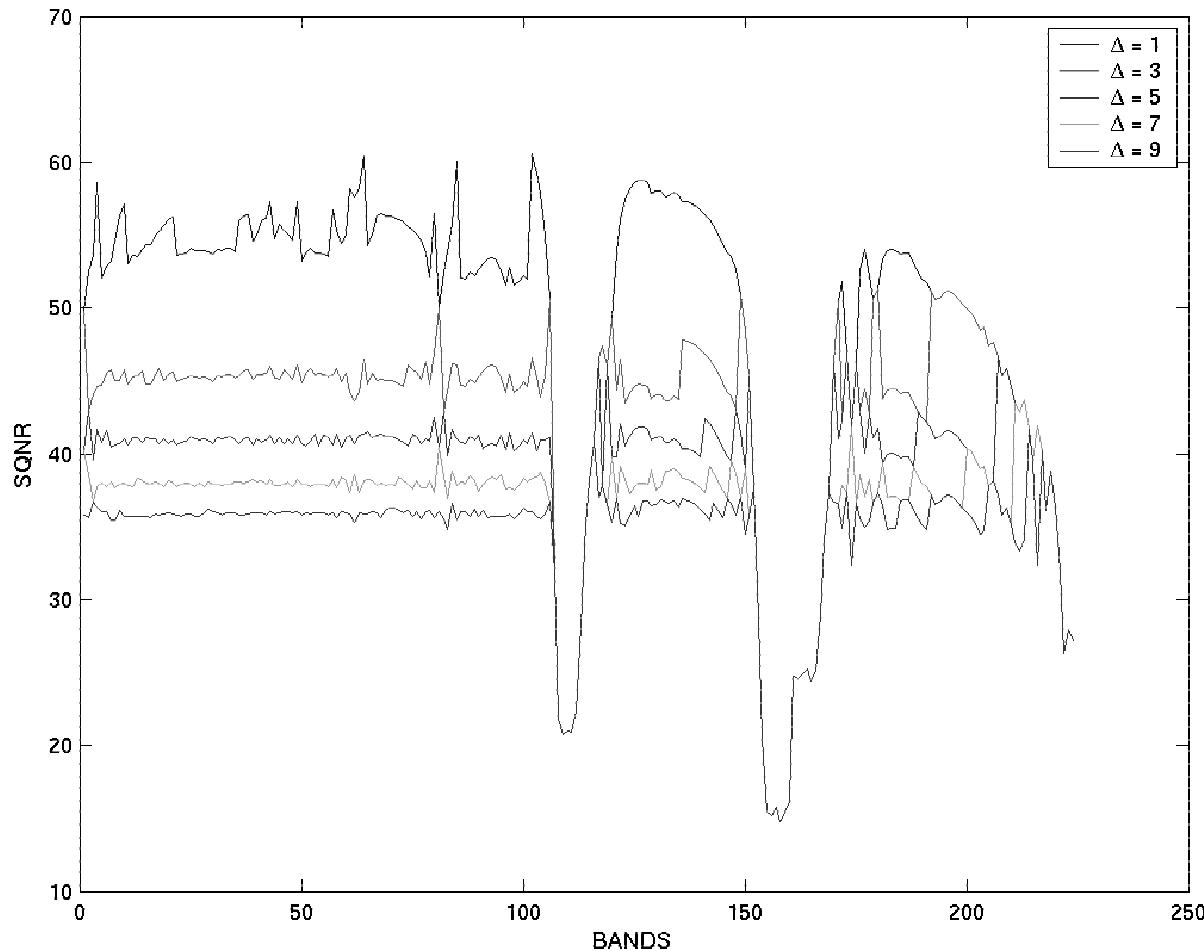
$$\begin{cases} 10 \log_{10} \frac{\xi_i^2}{(\Delta_i/2)^2} \approx 10 \log_{10} \frac{\xi_j^2}{(\Delta_i/2)^2} & \forall i, j \in [1, D] \\ \frac{1}{D} \sum_{i=1}^D \Delta_i = Q \end{cases}$$

Where

Δ_i = Maximum error for band i \square

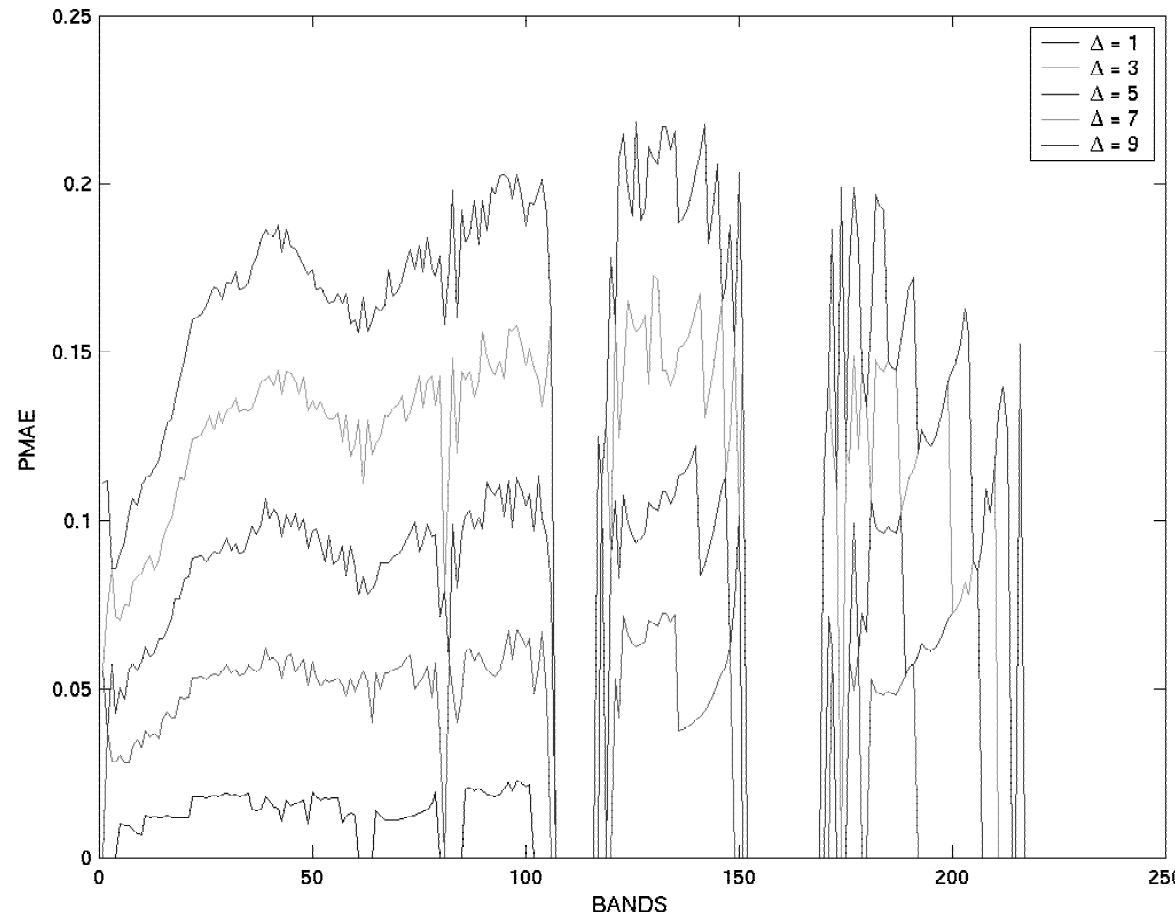
ξ_i = Average energy for band i \square

SQNR in Constant-SQNR Mode



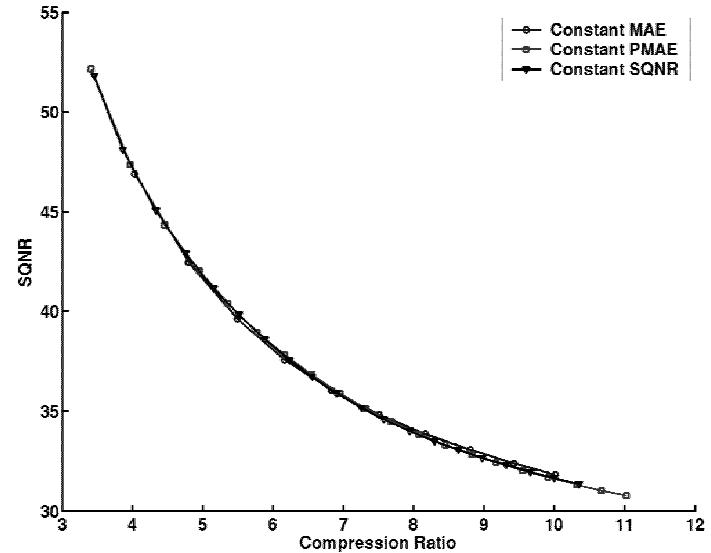
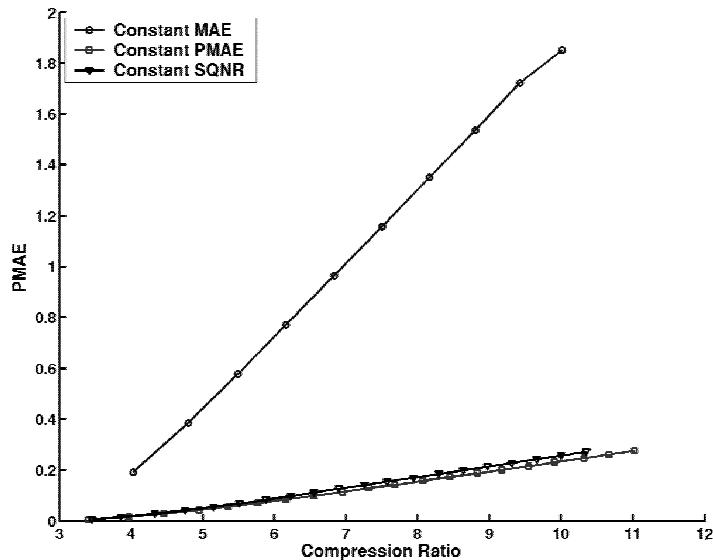
$$\text{SQNR(dB)} = \frac{10}{D} \sum_{i=0}^{D-1} \log_{10} \left(\sigma_{I_i}^2 / \sigma_{E_i}^2 + \frac{1}{12} \right)$$

PMAE in Constant-SQNR Mode



Note PMAE scale maximum 0.25 vs. 60

Near-lossless Modes



- Average PMAE drastically reduced with constant-PMAR/SQNR
- Average SQNR virtually identical in either mode

Conclusions

- Locally-optimal Partitioned Vector Quantizer
- Fast encoding/decoding (given the codebook)
- Natural parallelism
- Competitive performance
- Scalable, progressive coding
- Reduced resolution (indices only) can be used for classification and browsing
- Lossless and near-lossless modes for target detection